

# Evaluation of Sliding Mode Observers for Fault Reconstruction on the ADDSAFE Functional Engineering Simulator

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## ABSTRACT

This paper presents a preliminary evaluation of the results from using second order sliding mode observer schemes applied to an aircraft fault detection benchmark problem for a class of sensor faults. The scheme has been evaluated on the ADDSAFE Functional Engineering Simulator (FES). This is part of ongoing work on a European FP7 funded project entitled Advanced Fault Diagnosis for Sustainable Flight Guidance and Control (ADDSAFE) which aims to study advanced fault detection and isolation (FDI) methods for aircraft. The simulation and verification FES used in this evaluation incorporates a high fidelity nonlinear aircraft model from AIRBUS (which includes sensor and process noise). It is intended to provide a design tuning and assessment tool for the proposed FDI schemes developed within the ADDSAFE consortium and acts as a platform to test the robustness of the proposed schemes using a predetermined grid or sequence to cover a wide range of flight conditions and perturbations in the aircraft parameters. The FDI schemes will ultimately be evaluated in the Industrial Benchmarking and Verification FES which uses Monte Carlo methods to generate a statistical distribution and covers all of the desired flight conditions, perturbations and uncertainties in the aircraft parameters under investigation. This paper considers an LPV sliding mode observer for yaw rate measurement faults. A robust sliding mode reconstruction scheme for the aircraft lateral axis, based on an LPV system representation is presented. The sliding mode observers provide information about the unmeasurable signals (in this case the faults) through appropriate processing of the nonlinear injection signal required to maintain a sliding motion. The sliding mode LPV scheme utilizes LMIs to synthesize the gains of the observer to minimize the effect of

uncertainty on the reconstruction signal. The equivalent output error injection signals are obtained from a second order sliding mode structure, which is less susceptible to noise compared to the typical signum function associated with first order sliding. Preliminary evaluation results from the FES are presented for the yaw rate sensor fault to highlight the potential of the proposed scheme for fault detection and reconstruction.

## INTRODUCTION

A report by the European Commission [1] highlights the challenges for achieving 'green' aircraft. Recent technological advances such as composite materials for construction, high efficiency engines, optimized wing design for cruise, winglet, drag reduction, fly by wire actuators, all contribute to achieving these targets by reducing weight and drag, which in turn lowers fuel consumption. These technologies allow for sustainable green aircraft which are fuel efficient and thus have a lower carbon foot print and also lower cost per seat, therefore translating into an affordable cost for passengers. Another technology which contributes to the 'greening' of aircraft can be achieved through advances in fault detection and diagnosis. Although there seems to be no link between fault detection and diagnosis (FDD) and aircraft sustainability, it has been shown in [15] that improving the FDD performance in the flight control systems allows for better optimization of aircraft structural design and weight saving.

In current aircraft configurations, high levels of actuator redundancy are required to ensure sufficient availability of control. The same applies to sensor redundancy where triple redundant sensors are used to provide consistency checks to ensure optimum levels of performance in the event of sensor

faults. This high level of physical redundancy contributes to high production and maintenance costs, hydraulics and wiring complexity, and contributes to the weight of the aircraft. New innovative technologies such as fly by wire and electro hydrostatic actuators provide the same level of redundancy while ensuring lower weight and lower maintenance costs. Fly by wire also provides more design freedom which has been used to achieve low drag aircraft configurations as well as providing more freedom for fault tolerant control. However, with new technological advances, comes new needs for advanced fault detection and diagnosis to ensure the applicabilities of these technologies, while satisfying the current certification requirements [18]. This has motivated the creation of the ADDSAFE project.

The Advanced Fault Diagnosis for Sustainable Flight Guidance and Control (ADDSAFE) project is an European funded collaboration under the seventh Framework Programme (FP7) which started in July 2009 and is scheduled to end in July 2012. The aim of ADDSAFE is to demonstrate the applicability of advanced fault detection and diagnosis (FDD) methods for aircraft to support the development of sustainable aircraft. It represents challenges to improve the FDD which support new 'green' technologies allowing optimization of the aircraft structural design, improving aircraft performance and reducing the environmental footprint [18]. The consortium consists of members from 6 countries (Spain, UK, France, Germany, The Netherlands and Hungary) and includes the participation of industries (AIRBUS and DEIMOS space), research laboratories (DLR, SZTAKI and CNRS-IMS) and universities (University of Leicester, University of Hull and Delft University of Technology).

The work which is presented in this paper is part of an ongoing activity within the University of Leicester associated with the ADDSAFE project. One of the ADDSAFE benchmark challenges is to detect and identify faulty yaw rate sensors [13]. In the case when one of the sensors in the air data and inertial reference system (ADIRS) is faulty, consistency checks can be used to detect and isolate the faulty sensor. However, if two sensors are faulty, this potentially can become a problem as the consistency check will be likely to choose the two corrupt measurements instead [13]. For incipient sensor faults (e.g. bias), the controller might provide a small but nonzero control surface demand (due to the wrong measurement) which will increase drag and therefore over a period of time will significantly increase fuel consumption. Model based analytical redundancy can be used as the '4th' sensor to address this problem without requiring additional hardware. Although not considered in this paper, if the analytical redundancy is robust enough to provide good detection or isolation, it potentially allows for only two redundant hardware sensors and the analytical one becomes the '3rd' sensor. This offers the potential for further weight saving.

The FDD scheme which is considered in this paper is based on sliding mode concepts. Due to the natural robustness property of sliding modes and their ability to reconstruct faults, sliding mode observers have gained significant attention in the last few years. Reference [11] represents one of the earliest works which demonstrated the uncertainty/fault reconstruction capability of sliding mode observers. The next development in [22] included a rigorous analysis for robust designs, while the work in [7] considers the development of fault reconstruction of incipient faults and [23] proposed a cascaded observer approach to alleviate the relative degree requirement. These theoretical developments have shown the potential of sliding modes to handle different design and system requirements, and to provide not only detection of faults, but also information about the magnitude and shape through reconstruction. Recent developments in sliding mode controllers [5, 6] have shown the capability of sliding modes in terms of practical implementation. Successful piloted flight simulator tests have been carried out to evaluate the performance of the controller in the GARTEUR FM-AG16 project [9] which ended in 2008.

The latest development of the sliding mode FDD scheme in [22] includes an LPV formulation for the basis of designing an observer to provide fault detection and diagnosis. Theoretical work in [4] showed initial developments of LPV based fault reconstruction for actuator faults, while the work in [3] extended the idea to include robustness into the design. The LPV approach is motivated by the need to ensure validity over a wide range of the flight envelope. The LPV formulation is a natural extension to linear based designs compared to a full blown direct nonlinear approach. Difficulties in modelling the aircraft due to nonlinearities and the complexity of the aerodynamics reflected in the aerodynamic coefficients mean that an LPV model based approach is convenient to deal with, and is easily obtained, while maintaining a good level of fidelity compared to the nonlinear model. Furthermore the LPV methodology is a special case of gain scheduling, and therefore the concept can be easily grasped by a control design engineer.

The results presented here represent an initial evaluation of the scheme proposed in [3] on a functional engineering simulator (FES) provided by DEIMOS. The simulation is conducted on a predetermined grid or sequence to cover a wide range of flight conditions and perturbations in the aircraft parameters [12] in order to provide some design verification and performance assessment. These results will be used for fine tuning of the FDD in preparation for the evaluation process on the Industrial Benchmarking and Validation FES in DEIMOS [12], which uses Monte Carlo methods to generate the statistical distribution and covers all of the desired flight conditions, perturbations and uncertainties in the aircraft parameters.

# SENSOR FAULT BENCHMARK PROBLEM

Consider an LPV plant represented by

$$\dot{x}_p(t) = A_p(\rho)x_p(t) + B_p(\rho)u(t) + M_p\xi_p(t, y, u) \quad (1)$$

$$y_p(t) = C_p x_p(t) + N_p f_o(t) + d_p(t) \quad (2)$$

where  $A_p(\rho) \in \mathbb{R}^{n_n \times n_n}$ ,  $B_p(\rho) \in \mathbb{R}^{n_n \times n_m}$  are parameter varying matrices, while  $C_p \in \mathbb{R}^{n_p \times n_n}$ ,  $N_p \in \mathbb{R}^{n_p \times n_q}$  and  $M_p \in \mathbb{R}^{n_n \times n_k}$  are fixed matrices and  $n_q < n_p < n_n$ . Assume that the columns of  $N_p$  are from the standard basis for  $\mathbb{R}^{n_p}$  and has full column rank. The matrix  $C_p$  is assumed to have full row rank. It is also assumed that the inputs  $u(t)$  and the output measurements  $y_p(t)$  are available for the FDI scheme.

The signal  $f_o(t) \in \mathbb{R}^{n_q}$  represents the (unknown) vector of sensor faults. Here  $f_o \equiv 0$  is associated with fault-free conditions, while  $f_o \neq 0$  indicates a fault exists in the system and affects the measurements. Assume that an upper bound on the size of  $f_o$  is known and

$$\|f_o(t)\| < a(t) \quad (3)$$

where  $a(t) : \mathbb{R}_+ \mapsto \mathbb{R}^+$  is a known function. The signal  $d_p(t) \in \mathbb{R}^{n_p}$  represents a corruption of the true outputs and results in imperfect measurements even in the fault free case where  $f_o \equiv 0$ . A clear distinction is therefore to be made between the corruption represented by  $d_p(t)$  which is always present, and infrequent but serious corruptions/biases/drifts etc represented by  $f_o(t)$ . In this paper, it will be assumed that some of the sensors are fault-free while some are occasionally prone to exhibiting faults. This is a valid assumption since some sensors may be inherently less reliable or more vulnerable to external damage. It will be assumed that the signal  $d_p(t)$  is low pass in terms of its frequency content, so that from a frequency domain perspective

$$d_p(s) = G(s)\phi(s) \quad (4)$$

for some stable transfer function matrix  $G(s)$  with low pass filter characteristics. In (4) the driving signal  $\phi(s)$  is assumed to be unknown but bounded. It is the low frequency components of  $d_p$  that are likely to be mistaken for faults and result in false alarms and it is the distinction between  $f_o$  and  $d_p$  which is important in this paper.

The signal  $\xi_p(t, y, u) : \mathbb{R}_+ \times \mathbb{R}^{n_p} \times \mathbb{R}^{n_m} \rightarrow \mathbb{R}^{n_k}$  encapsulates the uncertainty in the system model. It is

assumed that  $\xi_p(\cdot)$  is unknown but bounded such that  $\|\xi_p(t, y, u)\| < b$  where the scalar  $b$  is known. In what follows it is assumed that the varying parameters  $\rho$  are known and  $\rho \in \Omega \subset \mathbb{R}^{n_r}$  where  $\Omega$  is a compact set (i.e. the components of  $\rho$  range between known extremal values  $\underline{\rho}_i < \rho_i < \bar{\rho}_i$  for  $i = 1; 2; \dots n_r$ ).

By permutating the order of the outputs, without loss of generality, it can be assumed that the plant representation is in a form

$$y_p(t) = \begin{bmatrix} y_{p,1}(t) \\ y_{p,2}(t) \end{bmatrix} \begin{matrix} \text{fault free} \\ \text{prone to fault} \end{matrix} = \underbrace{\begin{bmatrix} C_{p,1} \\ C_{p,2} \end{bmatrix}}_{C_p} x_p(t) + \underbrace{\begin{bmatrix} 0 \\ I_q \end{bmatrix}}_{N_p} f_o(t) + \underbrace{\begin{bmatrix} d_{p,1}(t) \\ d_{p,2}(t) \end{bmatrix}}_{d_p} \quad (5)$$

where  $C_{p,1} \in \mathbb{R}^{(n_p-n_q) \times n_n}$  and  $C_{p,2} \in \mathbb{R}^{n_q \times n_n}$ . This form will be used as the basis for the designs which follow. First filter the output  $y_{p,2}(t)$  to create the state  $z_f(t) \in \mathbb{R}^{n_q}$  according to

$$\dot{z}_f(t) = -A_f z_f(t) + A_f y_{p,2}(t) \quad (6)$$

where  $-A_f$  is a stable matrix of dimension  $\mathbb{R}^{n_q \times n_q}$ . Substituting for  $y_{p,2}(t)$  from (5) into (6) yields

$$\dot{z}_f(t) = -A_f z_f(t) + A_f C_{p,2} x_p(t) + A_f f_o(t) + A_f d_{p,2}(t) \quad (7)$$

Augmenting the subsystems in (1) and (7) gives a system of order  $(n_n + n_q)$  of the form

$$\underbrace{\begin{bmatrix} \dot{x}_p(t) \\ \dot{z}_f(t) \end{bmatrix}}_{\dot{x}(t)} = \underbrace{\begin{bmatrix} A_p(\rho) & 0 \\ A_f C_{p,2} & -A_f \end{bmatrix}}_{A(\rho)} \underbrace{\begin{bmatrix} x_p(t) \\ z_f(t) \end{bmatrix}}_{x(t)} + \underbrace{\begin{bmatrix} B_p(\rho) \\ 0 \end{bmatrix}}_{B(\rho)} u(t) + \underbrace{\begin{bmatrix} 0 \\ A_f \end{bmatrix}}_F f_o(t) + \underbrace{\begin{bmatrix} M_p & 0 \\ 0 & A_f \end{bmatrix}}_M \underbrace{\begin{bmatrix} \xi_p(t) \\ d_{p,2}(t) \end{bmatrix}}_{\xi(t)} \quad (8)$$

Create a new 'output' from the augmented system in (8) of the form

$$\underbrace{\begin{bmatrix} y_{p,1}(t) \\ z_f(t) \end{bmatrix}}_{y_m(t)} = \underbrace{\begin{bmatrix} C_{p,1} & 0 \\ 0 & I_q \end{bmatrix}}_C \underbrace{\begin{bmatrix} x_p(t) \\ z_f(t) \end{bmatrix}}_{x(t)} + \underbrace{\begin{bmatrix} d_{p,1}(t) \\ 0 \end{bmatrix}}_{d(t)} \quad (9)$$

In the above, the output is a combination of the actual and the filtered outputs (which are potentially prone to faults). The system represented in (9) and (8) is in the form of an actuator fault reconstruction problem. Note that by construction  $\text{rank}(CF) = n_q$  where  $C$  and  $F$  are defined in (9) and (8).

The observer for system (8)-(9) considered in this paper has the structure

$$\dot{\hat{x}}(t) = A(\rho)\hat{x}(t) + B(\rho)u(t) - G_l(\rho)e_y(t) + G_n\nu(t) \quad (10)$$

$$\hat{y}(t) = C\hat{x}(t) \quad (11)$$

where the gain matrices  $G_n \in \mathbb{R}^{(n_n+n_q) \times n_p}$  and  $\nu(t)$  is a discontinuous injection signal used to induce a sliding motion [11]. From (9) and (11) the output estimation error

$$e_{y_m}(t) = \hat{y}(t) - y_m(t) = Ce(t) - d(t) \quad (12)$$

where the state estimation error  $e(t) = \hat{x}(t) - x(t)$ . Subtracting (8) from (10) yields

$$\dot{e}(t) = A(\rho)e(t) - G_l(\rho)e_y(t) + G_n\nu(t) - Ff_o(t) - M\xi(t) \quad (13)$$

The design freedom in the observer will be selected to force the output estimation error  $e_{y_m}(t)$  to zero in finite time, to induce a sliding mode on the surface

$$\mathcal{S} = \{e \in \mathbb{R}^{n_n} : e_{y_m} = 0\} \quad (14)$$

If the measurement corruption term  $d(t) \equiv 0$ , and if the estimation error is constrained to the surface in (14), the output of the observer exactly follows the plant output. The idea is that, during sliding, the signal  $f_o(t)$  will be estimated using the concept of 'equivalent output injection' [10, 11, 22] which represents the signal  $\nu(t)$  must take on average to maintain sliding [24, 10]. As argues in [3] the fixed gain  $G_n$  is parameterized in terms of a design matrix  $L \in \mathbb{R}^{(n_n+n_q-n_p) \times n_p}$  with the structure

$$L = \begin{bmatrix} L_1 & 0 \end{bmatrix} \quad (15)$$

with  $L_1 \in \mathbb{R}^{(n_n+n_q-n_p) \times (n_p-n_q)}$ . The gain  $G_l(\rho)$  is parameterized in terms of a matrix  $\tilde{A}_{22}^s \in \mathbb{R}^{n_p \times n_p}$  which must be Hurwitz (see [3] for further details).

Define a reconstruction signal as

$$\hat{f}_o = W\nu_{eq} \quad (16)$$

where the fixed matrix  $W \in \mathbb{R}^{n_q \times n_p}$ . The gains  $G_n$ ,  $G_l(\rho)$  and  $W$  need to be chosen so that the  $\mathcal{L}_2$  gain between the uncertainty  $\xi$  and the estimation error  $\hat{f}_o - f_o$  is less than  $\gamma$ . This can be posed as an LMI optimization problem. For design, it is assumed that  $d(t)$  from (9) emerges from the exogenous model

$$\dot{d} = -a_f d + a_f \phi \quad (17)$$

where  $a_f \in \mathbb{R}^+$  where the unknown signal  $\phi(t)$  is assumed to be bounded. This is then integrated into the LMI optimization framework. To introduce additional design freedom, a weighting matrix

$$\Delta = \text{diag}(\delta_1, \delta_2) \quad (18)$$

where  $\delta_1 = \text{diag}(\delta_{1,1} \dots \delta_{1,n_k+n_q})$  and  $\delta_2 = \text{diag}(\delta_{2,1} \dots \delta_{2,n_p})$  will be used to balance between the requirement for the fault estimation to be insensitive to uncertainty in the plant  $\xi(t, y, u)$  and insensitive to the imperfect measurements  $\phi(t)$ .

As in [25], it will be assumed that (8) and (9) can be represented as a polytopic system where the range of admissible  $\rho$  corresponds to a polytope  $R$  with vertices  $\omega_1, \omega_2, \dots, \omega_{n\omega}$  where  $n\omega = 2^{nr}$ . As discussed in [25, 8], the affine LPV system matrices  $(A(\rho), B; C(\rho), F)$  in (8) and (9) can be replaced by  $(A(\omega_i), B, C(\omega_i), F)$  and the LMIs can be solved for all the vertices of the polytopic system.

For the injection term  $\nu(t) \in \mathbb{R}^{n_p}$ , consider a second order sliding mode output error injection  $\nu(t)$  where the  $j$ th component  $\nu_j$  satisfies

$$\nu_j(t) = -k_1 \text{sign}(e_{y_m,j}(t)) |e_{y_m,j}(t)|^{1/2} + z_j(t) \quad (19)$$

$$\dot{z}_j(t) = -k_3 \text{sign}(e_{y_m,j}(t)) - k_4 e_{y_m,j}(t) \quad (20)$$

where  $e_{ym} = \text{col}(e_{ym,1}, e_{ym,2} \dots e_{ym,np})$ . The variables  $k_1, k_3, k_4$  are design scalars. Note that (19)-(20) has a similar structure to the one in [19]. Provided  $\|\dot{\xi}_a\|$  and  $\|\dot{f}_o\|$  are bounded, if the gains from (19) and (20) are chosen as

$$k_1 > 2\sqrt{\varepsilon} \quad (21)$$

$$k_2 > 0 \quad (22)$$

$$k_3 > \varepsilon \quad (23)$$

$$k_4 > \frac{(k_2)^2 ((k_1)^3 + \frac{5}{4}(k_1)^2 + \frac{5}{2}(k_3 - \varepsilon))}{k_1(k_3 - \varepsilon)} \quad (24)$$

where  $\varepsilon$  is sufficiently large, then  $e_{ym} = \dot{y}_m = 0$  in finite time [19]. Then as argued in [23], the fault estimation signal  $\hat{f}_o$  satisfies

$$\hat{f}_o = f_o + G(s, \rho)\xi_a$$

where  $G(s, \rho)$  represents a manipulation of the LPV system in (8)-(9) depending on the choice of  $G_I$ .

## ADDSAFE BENCHMARK

The ADDSAFE benchmark is a SIMULINK based model provided by AIRBUS [13]. It represents a high fidelity generic twin engine civil commercial transport aircraft. It comprises the rigid-body aircraft model with a complex aerodynamic database, a full set of control surfaces, highly detailed nonlinear actuators and sensor models. The model is highly representative of the actual aircraft flight physics with realistic handling qualities [13] which include pilot side stick and pedals inputs, and a flight control law to provide closed-loop nonlinear aircraft autopilot capabilities.

## ADDSAFE BENCHMARK PROBLEM

One of the benchmark problems considered in ADDSAFE is a scenario involving a faulty yaw rate measurement. The sensor in the nonlinear ADDSAFE model has triple redundancy, and the actual measurement used for the controller is decided by a consistency check (vote) between the three individual sensor measurements [14, 16]. Note that simultaneous faults in two yaw rate measurements is considered very improbable by industrial standard. However for testing purposes, this condition is also considered during the simulation. If one of the three sensors is faulty, the voting scheme will be able to differentiate the faulty measurement and avoid it being used by the controller. However, if two of the sensors are faulty, the faulty measurement is likely to be

used instead and can result in higher fuel consumption over a long period of time due to non trim offsets of the control surfaces for incipient faults (such as a bias), or much worse, degradation in performance of the controller in the case of a severe sensor fault. The detection and isolation of a faulty yaw rate sensor is one scenario which will be investigated in the ADDSAFE project, and constitutes one of the benchmark problems to be tackled by the consortia.

## ADDSAFE LPV MODEL

The LPV plant used as a basis for the scheme presented in this paper is a lateral model provided by DLR [17]. The model is derived from the ADDSAFE benchmark model using an LPV generation procedure described in [20]. The method involves the generation of a set of linearized models at equilibrium/trim points which are enclosed in the range of the LPV parameters. The elements of all the state space matrices are then interpolated to generate a polynomial, fitted using least squares. The resulting polynomials can be used to create a single LPV model which approximates the whole set of LTI equilibrium models [17]. Further details of the LPV model and its generation are available in [17, 20].

In [17] the LPV parameters  $\rho$ , chosen to describe the variation of the aircraft dynamics, are mass ( $m$ ), centre of gravity in the x-direction ( $X_{cg}$ ), altitude  $h$ , and conventional airspeed  $V_{cas}$ . The LPV model is valid for variations of  $\pm 10\%$  for mass  $m$  and position of centre of gravity  $X_{cg}$ ,  $\pm 25\%$  for altitude  $h$  and  $\pm 19\%$  for conventional airspeed  $V_{cas}$  from the trim point

$$\begin{bmatrix} m(0) \\ X_{cg}(0) \\ h(0) \\ V_{cas}(0) \end{bmatrix} = \begin{bmatrix} 200,000(kg) \\ 30\%(\text{mac}) \\ 20,000(ft) \\ 290(kt) \end{bmatrix}$$

The states, outputs and control surface deflections for the LPV model are given in Table 1 and Table 2. For the design which will be presented in this paper, only the lateral model will be considered. The lateral states are

$$x_p = [\phi \ V_y \ p \ r]^T$$

which represent roll angle, velocity in the y-axis, roll rate and yaw rate. The lateral control surfaces are rudder, ailerons and spoilers (13 surfaces). Note that since  $V_y(t)$  is not one of the measured outputs of the aircraft, and in order to obtain a fixed output distribution matrix  $C$  (as in equation (2)),  $V_y(t)$  is approximated in real-time from the measurements of sideslip angle ( $\beta(t)$ ) and true air speed ( $V_{tas}(t)$ ) via the equation

$$V_y(t) = V_{tas}(t) \sin(\beta(t)) \quad (25)$$